Automatic Relative Radiometric Normalization for Change Detection of Satellite Imagery

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***Abstract*— Several relative radiometric normalization (RRN) techniques have been proposed till date most of which involve selection of pseudo invariant features whose reflectance are nearly invariant from image to image and are independent of seasonal cycles. Extraction of such points is quiet tedious and human operator has to provide mutual correspondence by choosing easily recognizable and time invariant points. In this paper, we intend to propose a new automatic radiometric normalization technique to select PIFs in panchromatic images known as Bin-Division Method. For multispectral images, MAD (Multivariate Alteration Detection) has been employed for selecting PIFs based on the assumption that MAD components are invariant to affine transformation. This, followed by robust linear regression constitutes the whole automatic radiometric normalization procedure.**

***Index Terms*— Pseudo-invariant features, Bin-Division Method, Canonical Correlation Analysis, MAD Transformation, Linear Regression, RMS Error criterion.**

I. Introduction

Radiometric differences introduced in multi-date images make it extremely difficult to assess actual changes as exuded by changes in spectral reflectance, which in turn, makes radiometric normalization a vital step in satellite image processing process like change detection and analysis. Radiometric normalization can be categorized as absolute and relative. Absolute normalization, though sophisticated and accurate, requires sensor calibration coefficients, an atmospheric correction algorithm and related input data like atmospheric measurements at the time of image acquisition which are very difficult to avail. This shifts our focus to RRN which involves normalizing the brightness values of the image, band-by-band to the reference image of a different acquisition date such that the two images seem to be acquired with the same sensor under similar atmospheric conditions. [1]. Non-linear correction, method like Histogram Matching is generally not preferred as they produce a lot of spectral variations which can be confused as actual changes [2].

Keeping this premise in mind, the normalization of subject image can be carried out as:

$$F'_s(x,y) = o + g * F_s(x,y) \qquad (1)$$

Where $F'_s(x, y)$ the normalized gray value of subject image is, $F_s(x, y)$ is the actual gray value and g,o are the normalization coefficients namely gains and offset values. Several relative radiometric normalization techniques like Pseudo-invariant features [3], Radiometri Control set [4], No Change set using scatter gram [5] have been proposed till date. These methods involve radiometric stable features known as Pseudo-invariant points to approximate the DN values. These features have same reflectivity even during different seasonal cycles and their brightness values are linearly distributed [3]. The Dataset used. The image dataset used in this study is obtained from IRS-1D satellite. The dataset comprises of two geometrically registered panchromatic images of same area taken on two different dates. For normalization of multispectral images, two geometrically registered images of another area taken on two different dates have been used. Fig.3 (a) & (b) as well as Fig.4 (a) & (b) show the dataset used.

III. Methodology

The whole process of relative radiometric normalization can be divided into three steps: (i) pre-processing (geometric registration); (ii) selection of pseudo-invariant features (iii) determination of normalization coefficients from selected PIFs.

A. Pre-processing: Geometric registration

Panchromatic and multi-spectral subject images are geometrically registered with the respective reference images before automatic relative radiometric normalization process.

B. Selection of Pseudo-invariant Features

In this article it is assumed that linear effects are much dominant than nonlinear and PIFs are those features in an image which are statistically invariant to any seasonal cycles; their reflectivity is almost linearly distributed in nature, either increasing or decreasing. They can either be bright set like urban features, concrete, rock structures etc or dark set like deep water bodies. [3] Following sections provide the description of proposed different approaches for pseudo invariant features:

1) Bin-Division Approach: Bin-Division is an effective method to separate PIFs features from a set of pixels in panchromatic images. It assumes the fact that radiance reaching at sensor can be related as linear function of reflectivity of target on ground. Using these assumptions, the pixels of subject and reference images are divided into three categories. This is based on the brightness value of a pixel of subject image which has either increased, decreased or has not changed with respect to the brightness value of the pixel at the same spatial position of the reference image. The corresponding pixels of both the images are placed in three bins.Let Fs(x, y) and Fr(x,y) are subject and reference

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images respectively.The bin divisions for both images pixels are as follows:

$$F_S(x,y)>F_R(x,y) \tag{2}$$
$$F_S(x,y)<F_R(x,y) \tag{3}$$
$$F_S(x,y)=F_R(x,y) \tag{4}$$

The pixels described by equation 2, 3, 4 are bin1, bin2 and bin3 respectively. The pixels which exist in bin1 and bin2 are combination of pixels which have experienced genuine land cover changes in their brightness values and radiometric changes. So bin1 is union of positively changed pixels and positive linear PIFs pixels and bin2 is union of negatively changed pixels and negative linear PIFs. The proposed Bin-Division methodology separate out PIFs from changed pixels in bin1 and bin2 assuming that the PIFs are linearly distributed. In Bin-Division method, our aim is to compute PIFs by minimizing the cost function that gives the linear similarity for corresponding pixels in bins. Let $f_s(x,y,n)$ and $f_r(x,y,n)$ are pixels in bins and $f'_s(x,y,n)$ are normalized values, then cost function is defined as Cost (1,2,3……n) = Dist $[f_r(x,y,n), f_s(x,y,n), f_s'(x,y,n), W(o,g)]$ for n values of bin. The PIFs are the pairs for which Cost(1,2,3…….n)<ä, ä a user defined threshold that sets the level of normalization. The minimization of cost function depends upon $\mathrm{Dist}[f_r,f_s,f'_s,W(o,g)]$ and weight W. The following section describes the determination of weight function algebraically. The objective of this method is to estimate the weights function W, for given $f_s(x,y,n)$ and $f_r(x,y,n)$, some knowledge of cost function. By assuming these quantities, it is possible to formulate a unified linear algebraic framework. The central of algebraic approach is the concept of finding a good estimate of weight function W which minimizes the predefined criterion of cost function defined by: $f_r - f_s(W) = C$.

In the absence of any knowledge of C, our need is to find a criterion function to find W such that $f_s(W)$ approximates f_r by assumption that norm of C is small as possible. In other words we wish to find out W such that criterion function $\|C\|^2=\| f_r - f_s(W) \|^2$ is minimized. The minimizing criterion function is $J(W) = \| f_r - f_s(W) \|^2$ with respect W. Minimizing this equation we get $\frac{\partial(J(W))}{\partial(W)} = 0 = -2f_s'(f_r - f_s(W))$ .Solving this equation, we get

$$W = f_r^{-1} f_s \tag{5}$$

The procedure is applied for each for 'Greater than' bin1 as well as 'less than' bin2 and pixels have residuals greater than a user-defined threshold were filtered out, leaving behind a final set of PIFs for both the bins. Closer the residual closer to the threshold value of 1, better would be PIFs. The plots shown in Fig.1 (a) and (b) show the linear nature of the final PIFs selected from both the bins.

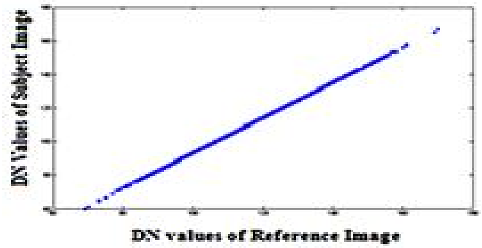

Fig.1.(a) A plot of PIFs selected for negative bin

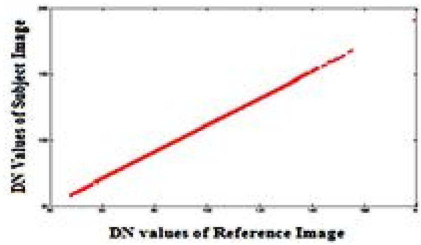

Fig.1.(b) A plot of PIFs selected by positive bin

Normalization coefficients are calculated for both the bins from the resultant PIF features. From equation 5 [9], normalization coefficients for both the bins are as follows:

$$o^+ = \frac{\left(\sum_{i=1}^{n^+} f_{s+}^2 \sum_{i=1}^{n^+} f_{r+}\right) - \left(\sum_{i=1}^{n^+} f_{s+} \sum_{i=1}^{n^+} f_{s+} f_{r+}\right)}{n^+ * \left(\sum_{i=1}^{n^+} f_{s+}^2\right) - \left(\sum_{i=1}^{n^+} f_{s+}\right)^2} \tag{6}$$

$$g^+ = \frac{n^+ * \left(\sum_{i=1}^{n^+} f_{s+} f_r\right) - \left(\sum_{i=1}^{n^+} f_{s+} f_{r+}\right)}{n^+ * \left(\sum_{i=1}^{n^+} f_{s+}^2\right) - \left(\sum_{i=1}^{n^+} f_{s+}^2 \sum_{i=1}^{n^+} f_{s+}\right)} \tag{7}$$

$$o^- = \frac{\left(\sum_{i=1}^{n^-} f_{s-}^2 \sum_{i=1}^{n^-} f_{r-}\right) - \left(\sum_{i=1}^{n^-} f_{s-} \sum_{i=1}^{n^-} f_{s-} f_{r-}\right)}{n^- * \left(\sum_{i=1}^{n^-} f_{s-}^2\right) - \left(\sum_{i=1}^{n^-} f_{s-}\right)^2} \tag{8}$$

$$g^+ = \frac{n^- * \left(\sum_{i=1}^{n^-} f_{s-} f_r\right) - \left(\sum_{i=1}^{n^-} f_{s-} f_{r-}\right)}{n^- * \left(\sum_{i=1}^{n^-} f_{s-}^2\right) - \left(\sum_{i=1}^{n^-} f_{s-}^2 \sum_{i=1}^{n^-} f_{s-}\right)} \tag{9}$$

Where $o^+,o^-,g^+,g^-,f_s^+,f_s^-,f_r^+,f_r^-,n_+,n^-$ are ordinates, gains, gray level values of subject, reference pixels and total number of pixels for respective bins. Using normalization parameters, normalized image is generated.

Bin-Division method works well even when temporal variations are significant and relies on the pixels function, which excludes pixels marked with spectral changes.

2) Multivariate Alteration Detection (MAD): In MAD automatic selection of PIFs is based upon the assumption that atmospheric and calibration differences are linearly related and MAD components are invariant to such affine transformations [7], [8]. This method is based on Canonical Correlation Analysis (CCA) [8].

Assuming [7] that we have two temporal images having N spectral channels, we can represent intensities of both images by random vectors F and G, where

$F=[F_1,F_2,F_3,\ldots\ldots\ldots\ldots F_N]^T$ *and* $G=[G_1,G_2,G_3,\ldots\ldots\ldots\ldots G_N]^T$

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Combining the intensities from all the bands linearly, we achieve

$U=a^TF=[a_1F_1+ a_2F_2+ a_3F_3+................ a_NF_N]$ (10)

$V=b^TG= [b_1G_1+ b_2G_2+ b_3G_3+............b_NG_N]$ (11)

The differences of the linear combinations U and V are known as MAD variates. Maximizing the difference information requires maximizing variance which requires minimizing the correlation between U and V under the Var(U)=Var(V)=1 with keeping the correlation as positive. Using CCA, searches for linear combinations $U=a^TF$ and $V=b^TG$ of the (ideally) Gaussian distributed variables [U,V]€N(μ, Σ .) with maximum correlation:

$$\rho=Corr[U,V] = \frac{cov[U,V]}{\sqrt{var[U]var[V]}} = \frac{a^T\Sigma_{1,2}b}{\sqrt{a^T\Sigma_{1,1}a}\sqrt{b^T\Sigma_{2,2}b}} \qquad (12)$$

This leads to the coupled generalized Eigen value problems

$$\Sigma_{fg}\Sigma_{gg}^{-1}\Sigma_{gf}\,a = \rho^2\,\Sigma_{ff}\,a \qquad (13)$$

$$\Sigma_{gf}\Sigma_{ff}^{-1}\Sigma_{fg}\,b = \rho^2\,\Sigma_{gg}\,b \qquad (14)$$

MAD Transformation is defined as the subtraction of canonical variates (solutions of (13) and (14)) . The MAD variates are uncorrelated to each other, the last component being maximally correlated with minimum difference information and first component having the maximum difference information.

Two images acquired under different atmospheric conditions with no genuine land cover differences will have a difference component with a nearly Gaussian distribution. Thus MAD components, in such cases have an uncorrelated Gaussian distribution. In case some land cover changes have occurred, the distribution will deviate more or less from its Gaussian nature.

Using suitable decision threshold, the non-difference pixels can be separated from changed pixels. Furthermore,[8] the sum of squared standardized MAD variates is chi-square distributed, which helps in setting the threshold as:

$$\sum_{i=1}^{N}\left(\frac{MAD_i}{\rho_i}\right)^2 \qquad (15)$$

where $t=\div^2_{p=0.01}$, with *P as* the probability of observing that value of *t* or lower. As long as the radiometric effects are linear, the pixels chosen can serve as PIFs. The plots shown in Fig. 2(a) and (b) depict nearly linear nature of PIFs for each band. The corresponding pixels values which are less than the threshold *t*, are PIFs for respective band.

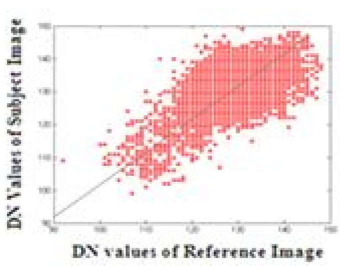

Fig.2.(a) A plot of PIFs for Band1

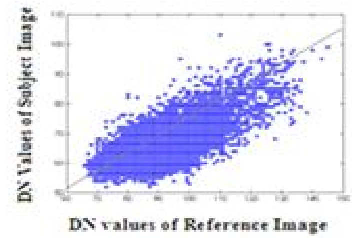

Fig.2.(b) A plot of PIFs for Band2

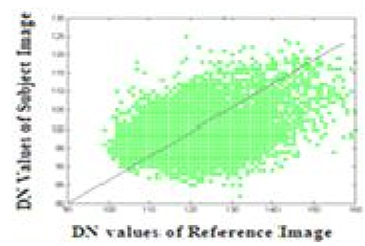

Fig.2.(c) A plot of PIFs for Band3

IV. RESULTS AND DISCUSSION

The quality of radiometric normalization in both the cases is statistically assessed using Root Mean Square Error (RMSE) which is defined as:

$$RMSE_k = \frac{\sqrt{\left(\sum_{j=1}^{N}(Subject_{jk}-Reference_{jk})^2\right)}}{N} \qquad (16)$$

Fig-3(a)-(c) and Fig-4(a)-(c), show panchromatic reference, subject, normalized subject images as well as MSS reference, subject, normalized subject images respectively. From Table-3 and 4,the RMS errors between the respective images(pan and mss) using proposed methods and other conventional methods can be seen. Numerically reduced RMSE after normalization in Table-3 One can observe that the RMS errors for proposed techniques are less as compared to other methods.

TABLE I: NORMALIZATION COEFFICIENTS FOR PANCHROMATIC IMAGE

	g(gain)	o(ordinate)
Positive	10.997	1.002
Negative	-11.512	0.954

TABLE II: NORMALIZATION COEFFICIENTS FOR MULTISPECTRAL IMAGE

Band No.	g(gain)	o(ordinate)
Band 1	1.776	-108.329
Band 2	1.198	25.606
Band 3	1.251	10.114

TABLE III: RSME USING BIN-DIVISION, HISTOGRAM MATCHING AND SIMPLE REGRESSION

	Root Mean Square Error
Before Normalization	14.36
Normalization (Bin-Division)	7.72
Normalization (Histogram Matching)	16.2923
Normalization (Simple Regression)	9.68

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TABLE IV: RSME USING MAD AND HISTOGRAM MATCHING

S.No	Before Normalization	After Normalization Histogram Matching	After Normalization (Using MAD)
Band 1	13.04	12.2	11.90
Band2	31.99	21.79	19.46
Band 3	28.80	19.63	17.6
Avg.	24.66	17.87	16.32

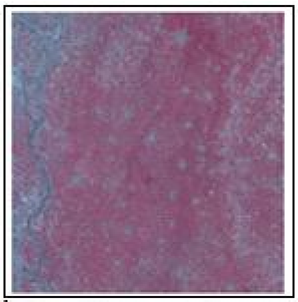

FIG 3(A): REFERENCE MSS IMAGE

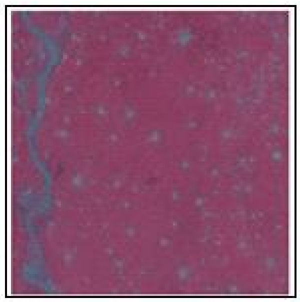

FIG 3(B): SUBJECT MSS IMAGE

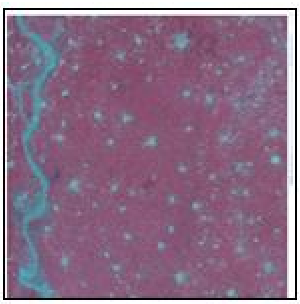

FIG 3(C): NORMALIZED MSS IMAGE

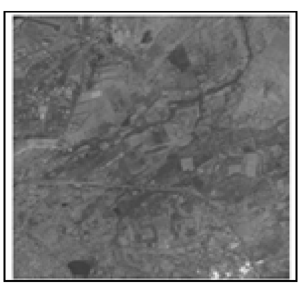

FIG 4(A): REFERENCE PAN IMAGE

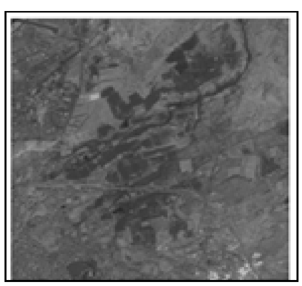

FIG 4(B): SUBJECT PAN IMAGE

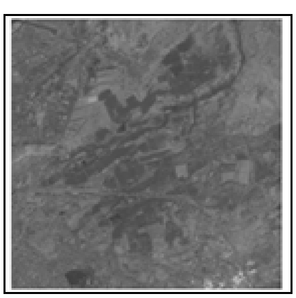

FIG 4(C): NORMALIZED PAN IMAGE

V. CONCLUSION

The proposed techniques for radiometric normalization are based on the assumption that atmospheric and calibration differences are linearly related and pseudo-invariant features are invariant with time or linearly increasing or decreasing

The techniques are computationally efficient and faster and are capable of radiometrically normalizing panchromatic as well as multispectral images automatically with least human intervention, except for selection of threshold and it also gives distributed sufficient number of PIFs over the radiometric range of image. Statistical assessment tools like RMSE as well as visual interpretation prove that both the techniques can be developed as powerful framework in removing radiometric differences between two images, making them more visually similar. Comparison with RMSE for Histogram Matching and Simple Regression prove our results further.

REFERENCES

[1] Gang Hong, Yun Zhang. Radiometric Normalization Of IKONOS Image Using QUICKBIRD Image For Urban Area Change Detection, Department of Geodesy and Geomatics Engineering, University of New Brunswick.

[2] Yang,Xiaojun, Lo,C.P.,(2000). Relative radiometric normalization performance for change detection from multi-date satellite images. Photogrammetic Engineering and Remote Sensing,66(8):967-980.RIFF Format. http://netghost.narod.ru/gff/graphics/summag y/micriff.htm.

[3] Schott,J.R.,Salvaggio,C.,Volchok,W.J.,(1988). Radiometric scene normalization using pseudo-invariant features. Remote Sensing of Environment, 26:1-16.William B. Penne baker, Joan L Mitchell, *JPEG Still Image Data Compression Standard*, Van Nostrand Reinhold, New York, NY, 1993.

[4] Hall, F.G., Strebel , D.E., Nickeson, J.E., Goetz , S.J.,(1991). Radiometric rectification: towards a common radiometric response among multidate, multisensor images, Remote Sensing of Environment, 35:11-27.

[5] Elvidge, C.D., D.Yuan, D.W. Ridgeway, R.S. Lunetta,(1995). Relative radiometric normalization of Landsat Multispectral scanner (MSS) data using automatic scattergram-controlled regression.

[6] Negi, D.S., Manocha, O.P., Jain, S.C. Region Based Registration Approach Combined with Invariant Moments and Invariant Property of Line Segments. Int. Conf. On Optics and Optoelectronics (2005).

[7] Canty, M. J., Nielsen, A. A., Schmidt M., (2004). Automatic radiometric normalization of multi-temporal satellite imagery. Remote Sensing of Environment, 91:4411-451.

[8] Hardoon, D. R., Szedmak S., Taylor, J. S. (2003). Canonical correlation analysis; An overview with application to learning methods. Technical Report: CSD-TR-03-02, Department of Computer Science, Royal Holloway, University of London.

[9] Press, W.H., Teukolsky, S.A., Vellerling, W.T., Flannery, B.P., (1992). Numerical recipes in C: The art of scientific computing. Second Edition. Cambridge University Press. 662p.

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